CLASSIFICATION OF LOMBOK SPECIAL PEARL QUALITY USING A COMBINATION OF FEATURE EXTRACTION AND ARTIFICIAL NEURAL NETWORK BASED ON FORM

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Abstract— Lombok is attracted to the Moto GP event, which is held annually. Various tourism brands are owned by the island of Lombok, one of which is Mutiara. The ideal Pearl is perfectly round and smooth, but there are a variety of other shapes as well. One method that can be used to process Pearl's image is Computer Vision. For that, it is necessary to have a way to classify the quality of a Pearl based on its shape. The purpose of this study is to propose a system for pearl image classification by combining feature extraction with artificial neural networks. The method used in this study is GLCM feature extraction and Neural Networks. The proposed system can provide good classification results by combining the GLCM method and the Neural Network. This study uses Epochs 5, 10, 15, 30, 50, 100, 200, 300, and 500 with a learning rate of 0.5. The results of this study indicate that Epoch 100 gives the highest accuracy, 91.66%.

Keywords: classification, Pearl, glcm, artificial neural network.

***Abstrak**—Lombok mempunyai daya Tarik dengan adanya pergelaran Moto GP yang diadakan setiap tahunnya. Berbagai brand pariwisata yang dimiliki oleh pulau Lombok salah satu diantaranya adalah Mutiara. Mutiara yang ideal adalah yang berbentuk sempurna bulat dan halus, tetapi ada juga berbagai macam bentuk lain. Salah satu metode yang dapat digunakan untuk memproses citra dari sebuah Mutiara adalah dengan menggunakan Computer Vision, untuk itu, perlu adanya suatu metode untuk mengklasifikasikan kualitas dari Mutiara berdasarkan bentuknya. Tujuan dari penelitian ini mengusulkan sebuah sistem untuk klasifikasi citra mutiara dengan mengkombinasikan antara ekstraksi fitur dengan Jaringan Syaraf Tiruan. Metode yang digunakan pada penelitian ini adalah ekstraksi fitur GLCM dan Jaringan Syaraf Tiruan, penelitian ini menggunakan Epoch 5, 10, 15, 30, 50, 100, 200, 300 dan 500 dengan learning rate 0.5. Sistem yang diusulkan dengan mengkombinasikan metode GLCM dan Jaringan Syaraf Tiruan mampu memberikan hasil klasifikasi yang baik. Hasil dari penelitian ini menunjukkan bahwa Epoch 100 memberikan hasil akurasi yang paling tinggi yaitu 91.66%.*

***Kata Kunci**: klasifikasi, mutiara, glcm, jaringan syaraf tiruan.*

INTRODUCTION

Lombok is one of the areas in the province of West Nusa Tenggara. It is a beautiful island with various tourist attractions and shopping centres for souvenirs as a keepsake for visitors who travel to the island of Lombok. Lombok has an added interest in the existence of the Moto GP event, which is held every year. The island of Lombok owns various tourism brands, one of which is Mutiara. Multiple types and models of pearls in Lombok have proven to be superior products that can penetrate national and international markets. Pearls are naturally formed by human cultivation (Meyer et al., 2013).

The ideal Pearl is perfectly round and smooth, but there are a variety of other shapes as well. The finest quality natural pearls have been highly valued as gemstones and objects of beauty for centuries (Akbar et al., 2017) and have been used for jewellery since ancient times (Cheng et al., 2021) and are among the gemstones that have received recognition from the world (Ozaki et al., 2021) and worldwide (Zhou et al., 2016). Currently, the primary method for calculating pearl form characteristics involves manually measuring the pearls' long and short axes with a vernier calliper (Liu et al., 2022). With so many types and models of pearls, not a few of the pearls produced by pearl cultivators are damaged, thereby reducing the quality of the pearls themselves. This damage cannot be seen with the naked eye, making it difficult for cultivators and buyers to distinguish the existing damages on Pearl. This damage can be detected and classified using the help of a computer system and visual tools and methods (Agatonovic-Kustrin & Morton, 2012). This damage can affect the quality and price of the Pearl itself. This damage also affects the colour of the Pearl itself, and this is because the colour of the Pearl is the most crucial feature of a pearl. The value of the Pearl depends on its quality and rarity (Tsai & Zhou, 2021). One method that can be used to process Pearl's image is Computer Vision (Tian, 2009). For that, it is necessary to have a method to classify the quality of a Pearl based on its shape.

Research on pearls using computer processing systems is still relatively low (Agatonovic-Kustrin & Morton, 2012). This study investigated the capacity of artificial neural networks to classify the quality of 27 different pearls from the UV-Visible spectrum. Spectral analysis was performed on each pearl sample at two locations to assess surface homogeneity. The spectral data (input) is pre-processed-processed to reduce noise, entered into the ANN, and correlated with the Pearl quality/sorting criteria (output). The results of this study indicate that the developed UV-Vis-ANN spectroscopy method can be used as a more objective method for assessing pearl quality and can be a valuable tool for the pearl grading industry. (Tian, 2009) This study uses computer vision to classify the quality of Pearls; Computer Vision is used to process pearl images after being transformed from RGB to HSV colour models, which can display the hue and colour depth information of Pearls. The proposed method was used for the first classification according to pearl surface colour and further classification according to Pearl saturation. (Akbar et al., 2017) This study uses the K-Nearest Neighbor method to classify the quality of pearls based on their shape and size. The final result obtained from this system can determine the grade and quality of pearls. From the data, there were 25 of 10 pearls of A quality, ten pearls of AA quality, and five pearls of AAA quality. Using the K-NN (K-Nearest Neighbor) method and the value of K = 1 can produce an accuracy rate of 92.30%. (Cheng et al., 2021) This study examines trends and developments in Mutiara using bibliometric network analysis in the last 25 years. Researchers conducted a bibliometric analysis of publications from the Science Core Collection Web Database from 1995 to 2020. This study reveals that their findings may serve as another way to understand research trends in mollusc pearl shells and contribute to future studies. (Agatonovic, 2015) using Probabilistic Neural Networks and UV Reflectance Spectroscopy as Pearl Quality Assessment Methods. From the research results, the developed model can predict the type of mollusc pearl. Researchers created a simplified model to produce more accurate pearl predictions. Research (Lapico et al., 2019) uses image processing to automatically measure a pearl's size. Current measurements with hands-on results in inaccuracy, slow processing, and unnecessary employee costs. Of the 2523 oysters used in this study, the researchers obtained 92.1% accuracy and reliability of the proposed system. This study (Xuan et al., 2018) proposed automatic pearl classification using the Convolutional Neural Network (CNN). The experimental results in this study show that, compared to vector machines and Neural Networks, MS-CNN gives better classification results by obtaining a classification result of 92.14% and an accuracy result of 91.24%. In addition, activation visualization of the convolutional kernel shows that MS-CNN can recognize Pearl features complexly.

From several previous studies, there has been no research that combines feature extraction and artificial neural networks to classify pearl images. Therefore, for this study, we propose a system for pearl image classification by combining feature extraction with artificial neural networks. The feature extraction used in this study is the Gray Level Co-occurrence Matrix (GLCM). GLCM is a feature extraction that provides good results for an image. (Pathak & Barooah, 2013). Before the training and testing stages are carried out, Mutiara's image is first acquired and pre-processed-processed.

MATERIALS AND METHODS

A. Image Data Retrieval

At this image-taking stage, Mutiara image data is taken directly from Mutiara cultivators in the Lombok area. Image data was taken using a DSLR camera with a distance of 15 cm. Image data taken is 60 image data, and each label is taken with four images from different retrieval, so the overall data used is 196 data. Figure 1 is an example of pearl image data that has been taken.

Figure 1. Example of data taken

B. Image Acquisition

At this stage, the image data is then acquired into several parts in the form of a polder, including the division for image A quality, AA Image quality, and AAA Image quality based on the quality of the Mutiara image itself.

C. Pre-processing

At this stage, after being made into several polders, the pearl image resulting from image retrieval is renamed Image A.1, Image A.2, etc. It is to simplify the training and testing process. Figure 2 is an example of the result of changing the file name.

Figure 2. Example of changing the filename

D. Training Data

Data training was conducted to learn the proposed method, in this case, the Gray Level Co-occurrence Matrix (GLCM) and the Artificial Terms Network (ANN). At this stage, the Epoch used is 5, 15, 30,50,100, 200, 300, and 500, while the Learning Rate used is 0.01. Figure 3 is an example of the training data dashboard display of the proposed application. Figure 4 is an example of the data training process that is carried out.

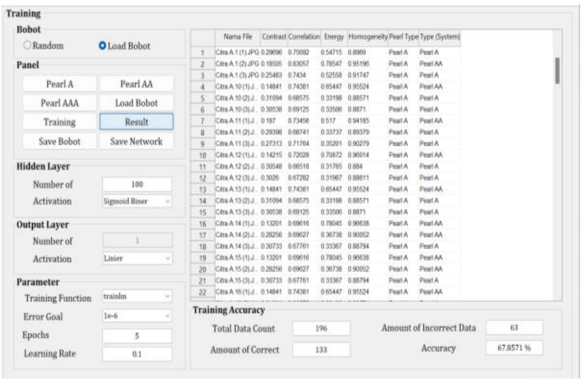

Figure 3. Training data dashboard

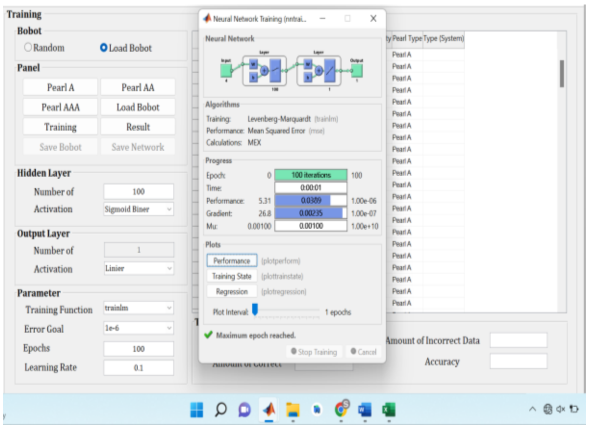

Figure 4. Example of the data training process

Figure 4 shows the data training process using Epoch 100, learning rate 0.1, 100 iterations, with a time of 0.00.01. An example of the results of the performance in the training process can be seen in Figure 5.

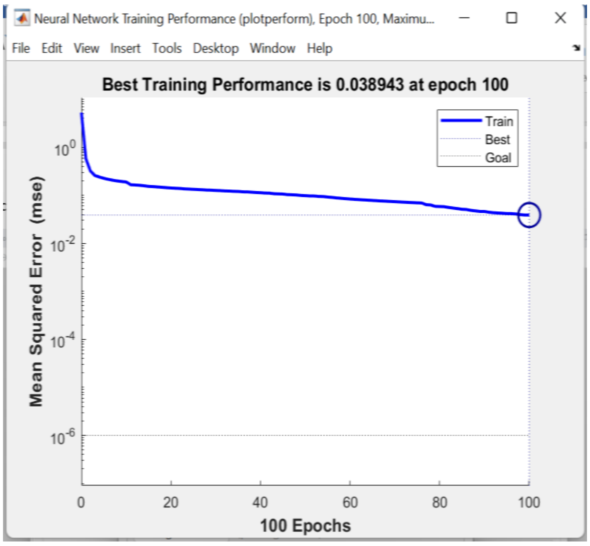

Figure 5. Performance of the training process.

E. Implementation of GLCM and Artificial Neural Networks

In this study, the image extraction method used is GLCM. Several studies concluded that the GLCM method could provide good extraction results (Alazawi et al., 2019; Suharjito et al., 2017). GLCM is a feature extraction method that uses texture calculations in the second order (Surya et al., 2017). The GLCM features used in this study are Contrast, Correlation, Energy, and Homogeneity. Figure 6 is an example of a classification dashboard of the proposed system.

Correlation

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ \frac{(i-m_r)\,(j-m_c)\,p_{ij}}{\vartheta_r\,\delta_c} \quad \text{.......................}(1)$$

Contrast

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ (i-j)^2 \, P_{ij} \quad \text{.......................}(2)$$

Homogeneity

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ P_{ij}^2 \quad \text{.......................}(3)$$

Energy

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \ \frac{P_{ij}}{1+[i-j]} \quad \text{.......................}(4)$$

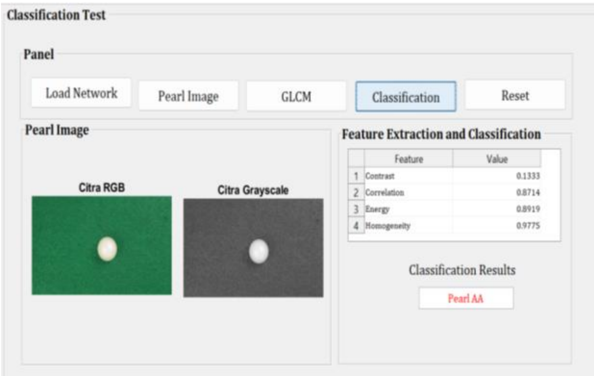

Figure 6. Classification dashboard

Figure 6 is an example of the proposed classification dashboard. First, determine the network created during the training process, select the image used for testing, and then the extraction process uses GLCM. The pearl image is converted into a grayscale image and displays the extraction results.

RESULTS AND DISCUSSION

A. Training and Validation

In this study, the software used in implementing the proposed system is Matlab Version R2020a. Then the supporting software in this study is the Windows 10 Operating System, Processor i7 Gen 11, and 8 Gb Ram.

Before the classification stage is carried out, we train pearl image data. Previously, the pearl image had been acquired and pre-processed-processed as needed. The total training data used is 196, while the epochs used are 5, 15, 30, 50, 100, 200, 300, and 500, with a learning size of 0.1. The results of the comprehensive training data, the epochs that show the highest accuracy are epochs 100, 200, 300, and 500. By using Epoch 5, we get 67.85% accuracy with 63 incorrect data, Epoch 15 gets 79.08% accuracy with incorrect data 41, Epoch 30 gets 85.20% accuracy with 29 incorrect data, Epoch 50 gets 88.26% accuracy with 23 incorrect data, Epoch 100 gets 100% accuracy with 8 incorrect data, Epoch 200 gets accuracy 100% with the number of incorrect data, namely 0, Epoch 300 gets 100% accurate results with the number of incorrect data being 0. Epoch 500 gets 100% accurate results, with the number of incorrect data being 0. The results of the training carried out as a whole can be seen in Table 1.

Table 1. Training results

Epoch	Iteration	Time Elapsed	Amount of Incorrect Data	Accuracy
5	5	00.00.01	63	67.85%
15	15	00.00.00	41	79.08%
30	30	00.00.00	29	85.20%
50	50	00.00.01	23	88.26%
100	100	00.00.01	8	100%
200	200	00.00.04	0	100%
300	300	00.00.06	0	100%
500	500	00.00.12	0	100%

In Table 1, the epochs that show the highest accuracy results are epochs 200, 300, and 500.

B. Evaluation of Results

The data used for testing are 48 image data. The data distribution is that 80% of the data is used as training, and 20% is used as testing. By using Epoch 5, the accuracy results obtained are 56.25%. By using Epoch 15, the accuracy results obtained are 56.25%. Epoch 30, the accuracy obtained is 66.66%. Epoch 50, the accuracy results obtained are 68.75%. With Epoch 100, The accuracy result obtained is 91.66%. By using Epoch 200, the accuracy results obtained are 83.33%. By using Epoch 300, the accuracy results obtained are 83.33%, while by using Epoch 500, the results obtained are 75%. The overall classification results can be seen in Table 2.

Table 2. Classification results

Epoch	Classification Result Accuracy
5	56.25%
15	56.25%
30	66.66%
50	68.75%
100	91.66%
200	83.33%
300	70.83%
500	75%

From the overall classification results, Epoch 100 gets the highest accuracy, 91.66%.

C. Discussion

We have conducted several experiments using more Epochs, such as Epoch 600, 700, 800, and Epoch 1000, with a learning rate of 0.1. In this study, we get the highest accuracy results using Epoch 100. However, we got lower accuracy results, so we used Epoch 5, 15, 30, 50, 100, 200, 300, and 500. Next is to compare the results of the method used with relevant research using the same object, namely the image of pearls. The results of the comparison can be seen in Table 3.

Table 3. Comparison of the classification method used with other methods.

Method	Accuracy
K-Nearest Neighbor (Akbar et al., 2017)	K 1 = 92.30% K 2 = 89.41% K 3 = 74.69%
Fluorescence Analysis (Tsai & Zhou, 2021)	100%
Probabilistic Neural Networks and UV Reflectance Spectroscopy (Agatonovic, 2015)	Correct classification = 90% Color classification = 90%
Image Processing (Lapico et al., 2019)	92.1%
#1 SVM BPNN MS-CNN #2 SVM BPNN MS-CNN (Xuan et al., 2018)	 85.19% 81.57% 92.14% 67.19% 62.52% 91.24%
Our method, GLCM + Artificial Neural Network	Epoch 5 : 56.25%, Epoch 15 : 56.25%, Epoch 30 : 66.66%, Epoch 50 : 68.75%, Epoch 100 : 91.66%, Epoch 200 : 83.33%, Epoch 300 : 70.83%, Epoch 500 : 75%

In previous studies, no research has combined GLCM and Artificial Neural Networks. For this reason, this study proposes a system to classify pearl image quality using GLCM and Artificial Neural Networks. From the classification test results, Epoch 100 got the highest accuracy, 91.66%.

CONCLUSION

The proposed method, by combining GLCM and Artificial Neural Networks in a classification system, can provide good classification results with high accuracy, as evidenced by the results of classification trials. Based on the results of the classification trials conducted using Epoch 5, 15, 30, 50, 100, 200, 300, and 500 with a learning rate of 0.1. The classification result showing the highest accuracy is Epoch 100, with 91.66%.

Several suggestions need to be made in further research. Namely, the pearl image used needs to be cropped so that it becomes smaller to facilitate the data processing, and the pearl image quality needs to be added to produce more diverse results. It is necessary to add training and testing data to get accurate results. Moreover, in the future development of the proposed system, class needs to be added to the quality of other images.

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